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Evaluation of laser based alignment algorithms under additive random and diffraction noise

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ABSTRACT

The purpose of the automatic alignment algorithm at the National Ignition Facility (NIF) is to determine the position of a laser beam based on the position of beam features from video images. The position information obtained is used to command motors and attenuators to adjust the beam lines to the desired position, which facilitates the alignment of all 192 beams. One of the goals of the algorithm development effort is to ascertain the performance, reliability, and uncertainty of the position measurement. This paper describes a method of evaluating the performance of algorithms using Monte Carlo simulation. In particular we show the application of this technique to the LM1_LM3 algorithm, which determines the position of a series of two beam light sources. The performance of the algorithm was evaluated for an ensemble of over 900 simulated images with varying image intensities and noise counts, as well as varying diffraction noise amplitude and frequency. The performance of the algorithm on the image data set had a tolerance well beneath the 0.5-pixel system requirement.

Keywords: centroiding, automatic alignment, image processing

1. INTRODUCTION

The LM1_LM3 algorithm determines the beam location by centroiding a series of light beam sources. The algorithm dynamically sets important processing parameters such as threshold and smoothing kernel size. As the noise power of the image increases the smoothing kernel adjusts in size to attenuate high frequency noise. For a nominal image, spot amplitude should be between 100 and 225 counts with spot diameter between 10 and 20 pixels FWHM; the noise should be less than 20 counts rms. A sample image satisfying this requirement is shown in Fig. 1.

Fig. 1: Real two beam light source alignment image processed by LM1_LM3 algorithm

2. NOISE SIMULATION

The real image as shown in Fig.1 is used to create three simulated images with maximum amplitudes of 50, 100, and 200. White Gaussian noise with an rms magnitude of 10, 20, and 50 is added to the images to create an ensemble of 900 images. [1] Figs. 2, 3, and 4 represent three such images from the ensemble with maximum amplitude and noise pairs as (200,10), (200,20), (200,50). Taking sets of 100 images for each signal and noise pair, the algorithm evaluates the position of the two spots. The statistics of one of the two spots are analyzed. The standard deviation of spot positions multiplied by three is taken as the measure of uncertainty. A second set of simulated images was also created with diffraction noise (Figs. 5-7). Note 1 λ indicates that the period of the diffraction noise is equal to the diameter of the spot.

These uncertainty values obtained from the Gaussian noise simulation are plotted as shown in Fig. 8. The graph shows that for all noise counts the uncertainty remains below 0.25 pixels. As the signal amplitude decreases or the noise rms increases, the uncertainty increases. The real application of the graph in Fig. 8 is its use as a measure of the uncertainty from real-time operations of NIF laser beams. By estimating the noise and signal from a real image, the data in Fig. 8 is used as a look up table to estimate the uncertainty. The exact value of the uncertainty is calculated by interpolation from the look up table.

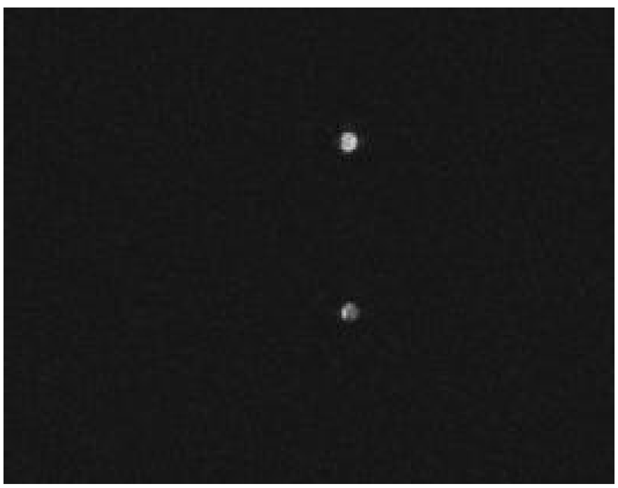

Fig. 2: Intensity Max 200, Noise 10 rms

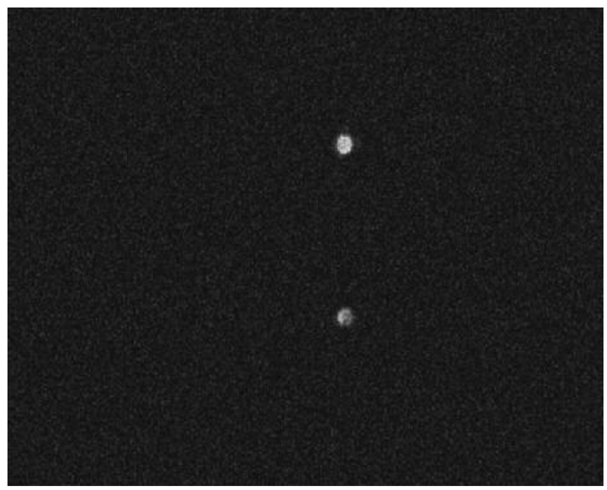

Fig. 3: Intensity Max 200, Noise 20 rms

Algorithm performance for simulated diffraction noise is presented in Fig. 9. The approach for ameliorating effects of diffraction noise while maintaining accuracy for centroiding was based on decreasing threshold value until an accurate centroiding was accomplished.

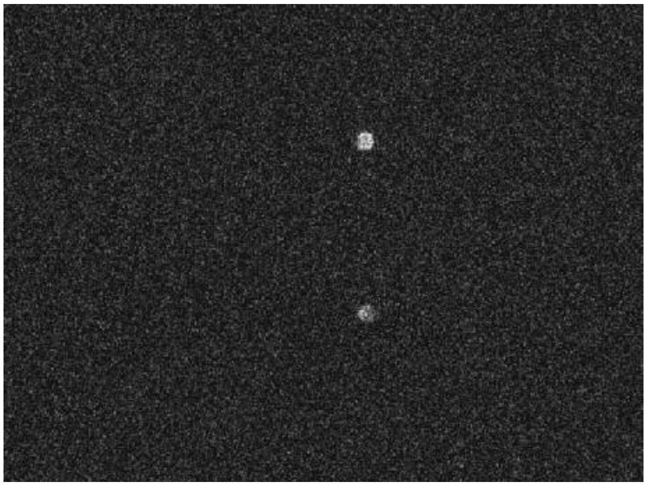

Fig. 4: Intensity Maximum 200, Noise 50 rms

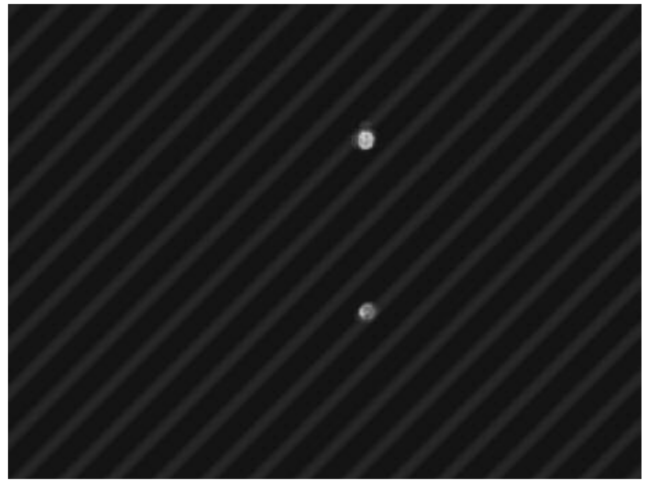

Fig. 5: Intensity 20, Interference Amplitude 200, P½λ

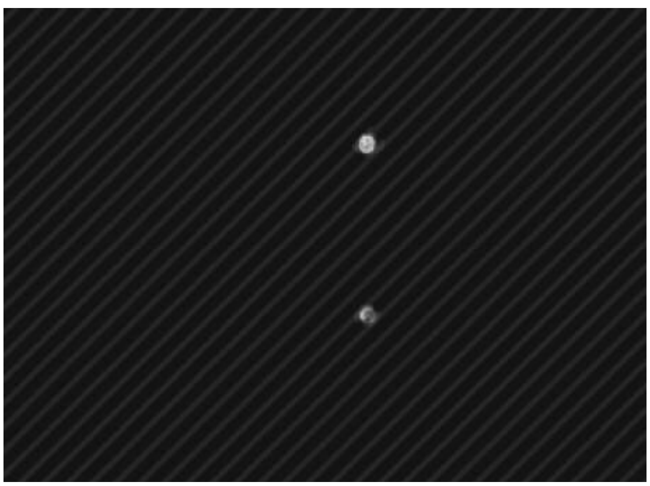

Fig. 6: Intensity 20, Interference Amplitude 200, Pe 1λ

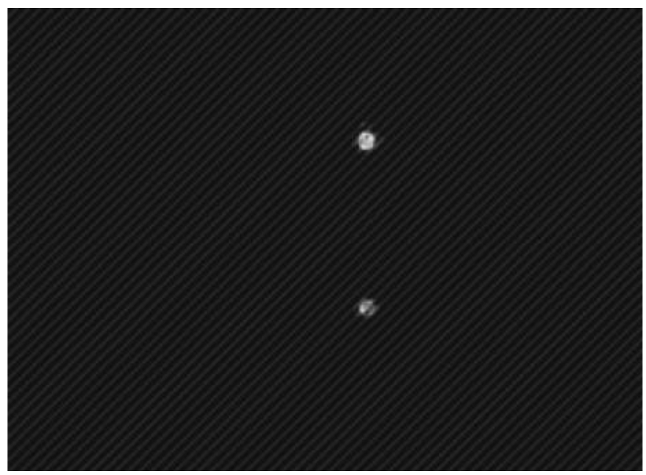

Fig. 7: Intensity 20, Interference Amplitude 200, Pe 2λ

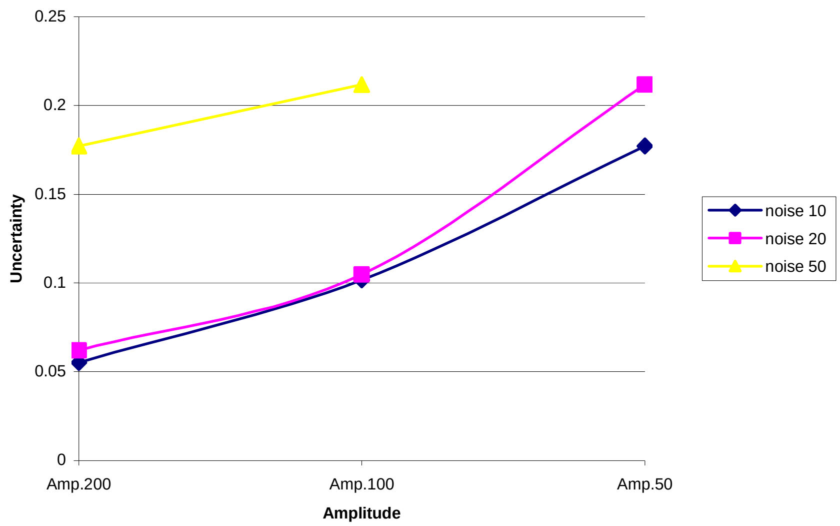

Fig. 8: LM1_LM3 algorithm Noise vs. Uncertainty Amplitude 200, 100, 50 with noise counts 10, 20, and 50

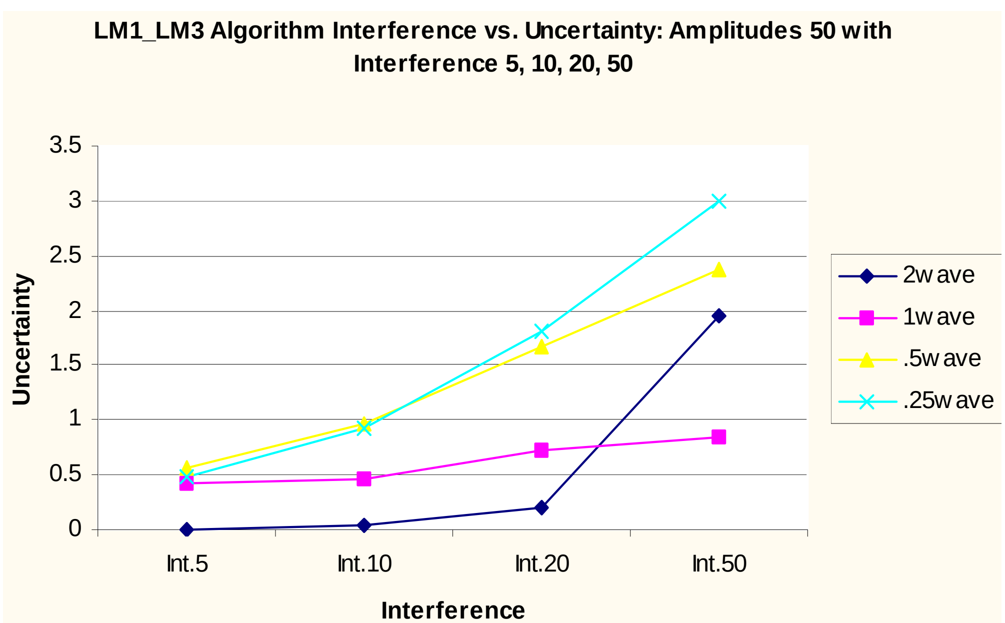

Fig. 9: Algorithm Interference vs. Uncertainty: Amplitude of 50 images

3. CALCULATION

The results presented in the previous section represent the uncertainty due to random and diffraction noise. The two uncertainty numbers are combined in cases where the algorithm chose the higher of the two. In this algorithm, there is a third uncertainty component based on spacing between the two bright spots. If the spacing between the two centroids is not within certain pixels of the expected values it indicates a displacement of some opto-mechanical components, which must be inspected before the alignment can be carried on. Our mechanism for achieving this is to raise the uncertainty level, which automatically shuts down the alignment system until an operator has examined the situation. The mathematics of this uncertainty measure are described below:

$$\begin{array}{lll} & & \otimes \\ \otimes & & \Downarrow \\ \Downarrow & & \Downarrow s \\ \Downarrow d & & \Downarrow \\ \otimes & & \Downarrow \\ & & \otimes \end{array}$$

Fig. 10: Expected vertical distance

As shown in Fig. 10, the expected vertical distance is *s* and the measured distance is *d*. The difference of (*s* - *d*) enters the uncertainty equation if it exceeds a tolerance threshold. Thus if (*d* - *s)* is 10, then we may not want to flag this situation. However, if it exceeds a tolerance threshold of 20, then the uncertainty will be divided equally between the two-centroid locations. The high uncertainty will be utilized to prompt an operator to check the hardware used to create the alignment pattern for maladjustment.

if (tolerance threshold) $\leq \mathrm{T}$

Uncertainty = higher (noise uncertainty, interference uncertainty)

else

$$= \left|\frac{(s-d)}{2}\right| \tag{1}$$

4. CONCLUSION

The LM1_LM3 algorithm performance is based on the principle of a normal distribution for an ensemble of images with differing noise and amplitude counts. The ensemble of images for each respective amplitude and noise data set produces a cumulative fraction of the causes, which gives the maximum variance. This principle is known as the “central limit theorem” [1].

For amplitude counts of 50 and noise counts of 50, the LM1_LM3 algorithm failed to centroid in the 100-image data set due to high amplitude distortion caused by high noise count. For other cases the radial standard deviation for each image data set produced results that yielded a maximum of approximately 0.3-pixel radial deviation (well within +/-0.5-pixel tolerance). However, it should be noted that the 0.3-pixel deviation was due to simulated image data with amplitude distortion and extremely high noise counts, none of which are anticipated in NIF. The algorithm can dynamically adjust for such high noise power occurrences and increases the size of the smoothing kernel to automatically adapt to noise and amplitude distortion. The uncertainty numbers calculated from the real images based on these simulated experiments, allow NIF alignment system operators to have confidence in the alignment process. A high uncertainty due to high noise or mechanical failure is caught by the system, notifying the operator to check the opto-electro-mechanical system. This uncertainty is important for avoiding expensive system failures. One of the problems of the current model however is that noise modeled as Gaussian may not be representative of realistic noise in the system. Future work for algorithm evaluation will involve the use of noise modeling using a realistic statistical model and probabilistic analysis of position distribution [2].

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